Terminal Cooperation using Game Theory for Energy Efficiency in Radio Access Networks: A Simulation Based Performance Analysis

Sathyanarayanan Chandrasekharan
School of Engineering,
RMIT University
Melbourne, Australia
s.chandrasekharan.2014@ieee.org

Sithamparanathan Kandeepan
School of Engineering,
RMIT University
Melbourne, Australia
kandeepan@rmit.edu.au

Karina Mabell Gomezline
School of Engineering,
RMIT University
Melbourne, Australia
karina.gomezchavez@rmit.edu.au

Akram Al-Hourani
School of Engineering,
RMIT University
Melbourne, Australia
akram.hourani@rmit.edu.au

Laurent Reynaud
Orange Labs
Lannion, France
laurent.reynaud@orange.com

Yvon Gourhant
Orange Labs
Lannion, France
yvon.gourhant@orange.com

***Abstract*— Energy efficiency of radio access communication systems is an important aspect of the 5G communication framework as defined in the IMT2020 specifications. In this paper we study game theoretic approaches for minimizing the energy consumption of radio access networks using terminal cooperation. The strategies for energy efficient transmissions through relay based communications (terminals cooperating with each other) is presented and compared against a centralized approach. Simulations are conducted to show the performance variations in the energy efficiency of the considered strategies.**

Keywords*— *energy efficiency, terminal cooperation, game theory

I. INTRODUCTION

Communications is becoming increasingly important as we traverse through the information age. This is exemplified by the breathtaking advances made in the field of communications engineering especially wireless communications. As the operators are commissioning the fourth generation of mobile communications systems, there has been increasing interest in the 5th generation of mobile communications shown by the researchers and industry alike.

The expectations from the 5th generation of mobile communications are sky-high in terms of the capacity, latency and coverage. This is possible only by combination of different advanced technologies such as cooperative communications, massive MIMO, dynamic spectrum access, etc. Also, the network operators are moving towards regional areas from saturated urban areas to increase their subscriber base. Energy efficiency is one of the core requirements in the 5G systems framework as per the IMT2020 specifications, as such the improvement in energy efficiency will reduce the carbon footprint in the environment in the long term and increase the battery lifetime of handheld devices in the short term. In this paper, we investigate different strategies for terminal cooperation to improve the energy efficiency. We refer to terminal cooperation where one handheld terminal acts as a relay terminal to transmit the information to the destination from a source terminal.

Energy efficiency in wireless communications is a well-treated topic in the literature [5-14]. The energy efficiency is addressed at all layers of the communications stack starting from the PHY layer at the component and the transmissions layer, at the MAC layer, and at the NET layer. The energy efficiency improvement at the MAC layer is the main focus of this work by also considering a relevant PHY layer model for the systems. In [1], the authors present their approach for maximizing energy efficiency with a cloud radio access network. The authors in [7] present an energy efficient downlink power and bandwidth allocation mechanism.

In this paper we adopt the game theoretic techniques from [5] and [8] to study their application on energy efficiency for the chosen wireless environment, and in terms of energy efficiency. In [5] the authors study the second price auction model for power trading, and in [8] the authors present a generic truthful auction based game theoretic model for cooperative communications. These methods are adopted to achieve energy efficiency in our work. Moreover we also consider a centralized approach and compare it against the distributed approach of using game theoretic strategies.

The remainder of the paper is organized as follows. In Section II we present the network and the system model adapted in our work. In Section III we present the game theoretic models adapted to energy efficiency, and in Section IV simulation results are presented to study the performance of the chosen strategies. Finally we draw some concluding results in Section V.

II. NETWORK AND SYSTEM MODEL

The network model adopted in our work includes three types of radio/wireless nodes, source nodes, relay nodes and one destination node, which models a typical uplink of a radio access network where the destination nodes are the base stations, as depicted in Figure-1.

We consider N source nodes denoted by $S_j, j = 1, 2, \dots, N$, K relay nodes denoted by R_k, $k = 1, 2, \dots, K$ where the destination node is denoted by D. The received signal between any two nodes, $S_j \rightarrow R_k$, $R_k \rightarrow D$, and $S_j \rightarrow D$, ignoring the subscripts, can be given as,

For the published version please see IEEE Explore

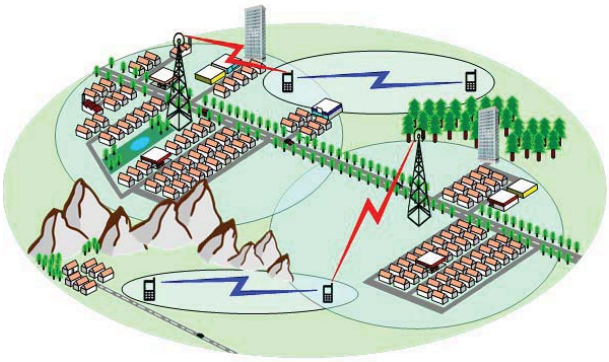

Fig. 1. The radio access network and system model with terminal cooperation

$$r(t) = \frac{1}{\sqrt{L(d)}} h(t)s(t) + v(t) \quad (1)$$

where, $s(t)$ is the transmitted signal, $h(t)$ represents the small scale fading channel, $v(t)$ is the additive noise at the receiver with a double-sided power spectral density of $N_0/2$, and $L(d)$ is the mean path-loss due to the transmitter-receiver (T-R) separation of d meters. For the links $S_j \rightarrow D$ and $R_k \rightarrow D$, we use the path-loss model suggested by WINNER II project [2] for the rural macro-cell, given by,

For LOS	$\mathrm{L(d)} = 40.0\log_{10}(\mathrm{d}) + 10.5 - 18.5\log_{10}(\mathrm{h_{BS}}) - 18.5\log_{10}(\mathrm{h_{MS}}) + 1.5\log_{10}(\mathrm{f_c}/5.0)$	(2)
For NLOS	$\mathrm{L(d)} = 25.1\log_{10}(\mathrm{d}) + 55.4 - 0.13(\mathrm{h_{BS}} - 25)\log_{10}\left(\frac{}{100}\right) - 0.9(\mathrm{h_{MS}} - 1.5) + 21.3\log_{10}(\mathrm{f_c}/5.0)$	(3)

where, d is the distance between the transmitter and the receiver in metres, h_{BS} and h_{MS} are the effective antenna heights at the base station and mobile terminals respectively and f_c is the carrier frequency in GHz. The shadow fading standard deviation for a rural environment in WINNER II is given by,

TABLE I. SHADOW FADING STANDARD DEVIATION FROM [2]

LOS	4 dB	when 10m < d < d_{BP}
	6 dB	when d_{BP}< d <10 km
NLOS	8 dB	

where d_{BP} is the breakpoint distance which is given by (fc is the centre frequency in Hz in this equation and c is the speed of light in m/s),

$$d_{BP} = 4\, h_{BS}\, h_{MS}\, f_c/c \quad (4)$$

For the link $S_j \rightarrow R_k$, we use the log-distance path-loss model given by,

$$L(d) = L(d_0) - 10\gamma \log_{10}\left(\frac{d}{d_0}\right) \quad (5)$$

where, γ is the path-loss exponent, d is the distance in meters between the S_j and R_k, and d_0 is the reference distance and $L(d_0)$ is the reference distance path-loss whose values are given in [3]. In all the links, we consider slow and fast fading channel modelled as a Rayleigh process whose mean channel power gains are given by,

$$\overline{h^2} = \frac{1}{t}\int_0^t h^2(t)\, dt \quad (6)$$

We assume context awareness at the nodes such that the above mentioned parameters such as T-R separations d, the channel power levels $\overline{h^2}$, the path-loss exponents γ are known to the respective nodes. Moreover, we assume decode-and-forward relaying protocol in our work. Note that the proposed model can be extended to any other cooperation protocol such as amplify-and-forward, etc. We consider binary DPSK communication system with QoS constraints such as BER and data rate to illustrate the game models for the energy efficiency/coverage objective. The bit error rate probability under Rayleigh fading with AWGN, ignoring the subscripts, is given by (Rappaport, 1996),

$$\Pi = \frac{0.5}{1 + \Gamma} \quad (7)$$

where, $\Gamma = E_b\overline{h^2}/N_0$ is the average SNR, E_b is the bit energy given by $E_b = \frac{P^t}{L(d)\Delta}$, and Δ is the data rate of the respective links. Moreover, if we consider $\overline{\Pi}$ to be the overall bit error probability for the communication on $S_j \rightarrow R_k \rightarrow D$ link, and Π_S and Π_R are the BER for $S_j \rightarrow R_k$ and $R_k \rightarrow D$ links respectively, then $\overline{\Pi} = \Pi_R(1 - \Pi_S) + \Pi_S(1 - \Pi_R)$. Since $2\Pi_S\Pi_R$ can be ignored (small value), the BER becomes,

$$\overline{\Pi} = \Pi_S + \Pi_R \quad (8)$$

III. GAME THEORETIC APPROACHES FOR ENERGY EFFICIENCY

We consider different types of game theoretic approaches for improving the energy efficiency of the considered radio access network model, as presented below.

A. Game Model 1 - Energy Trading Game

In this section, we present the energy trading game (Kandeepan, Jayaweera, & Fedrizzi, 2012) for multiple source terminals and multiple relay terminals in which the relay terminals trade energy with the source terminals to increase the energy efficiency of the source terminals. The source nodes requiring cooperation broadcast their cooperation requests with the QoS constraints. The QoS constraints considered in this work include data rate and bit error rate probability. The relay terminals respond with their bids to the base station. The base station applies the game model and sends the results to the winning relay nodes which inform the source terminals. We present the multi-source multi-relay first price sealed bid procurement auction model to improve energy efficiency at the source terminals. We define the game as $G = < I, A, \Omega >$ where I is the set of players in the game such that $|I| = N + K$, A is the Cartesian product of set of actions available to each player and $\Omega = \left\{\Omega_{S_j}, \Omega_{R_k}\right\}, j = 1, 2, \ldots, N$ and $k = 1, 2, \ldots, K$.

Source nodes: The reward function of the source nodes is given by,

$$\Omega_{S_j} = \Lambda E_d - C_{k,j} \quad (9)$$

where, Λ is the base cost in Dollars/Joule known to every node in the network, E_d is the energy required by the source terminal to directly communicate with the base station for T_{CP} seconds and $C_{k,j}$ is the cost to the source node S_j to cooperate with the relay node R_k. Equation (9) can be further simplified to,

$$\Omega_{S_j} = \Lambda P_{0,j}^t T_{CP} - C_{k,j} \quad (10)$$

where, $P_{0,j}^t$ is the power required to reach the base station directly from the source terminal S_j to achieve the data rate Δ_{S_j} with BER ξ_j, T_{CP} is the cooperation period in seconds. The cost $C_{k,j}$ in equations (9) can be given as,

$$C_{k,j} = \Lambda P_{k,j}^S T_{CP} + \alpha_{k,j} \quad (11)$$

where, $P_{k,j}^S$ is the power that needs to be transmitted by the source node S_j to relay R_k during the cooperation and $\alpha_{k,j}$ is the payment that the source node S_j needs to pay relay node R_k for its cooperation.

The source node could utilize different strategies based upon its local policy such as minimizing its transmit power thus saving energy or minimizing the payment made to the relays thus saving money. For coverage improvement, we can restrict the maximum transmit power of the source terminal. However, for energy efficiency purposes, we do not restrict the source terminals' transmit power. Thus, we consider the source nodes to minimize its cost $C_{k,j}$, thus given by,

$$\max_k \{\Lambda P_{0,j}^t T_{CP} - C_{k,j}\}, s.t.\ (C_{k,j}) < \Lambda P_{0,j}^t T_{CP} \quad (12)$$

Thus, the source nodes try to maximize their reward. However, if the cost of all relay nodes are higher than $\Lambda P_{0,j}^t T_{CP}$ then the source node declines all bids as cooperation is deemed to be infeasible (more expensive than directly communicating with the base station).

Relay nodes: We assume that all the relay nodes are aware of the source nodes' strategy to select the relay nodes given by () i.e. to minimize cost. After receiving all the cooperation requests from the source nodes, the relay nodes: (i) calculate their bids to the source nodes, and (ii) select which source nodes to send their bids corresponding to their maximum transmit power constraint $P_{R_{k,max}}^t$.

We first explain how the relay nodes calculate their bids. The bid sent by the relay node to a source node consists of a tuple given by $< \widehat{P_{S_j}^t}, \widehat{\alpha_{k,j}} >$. To calculate the bid for each source node, the relay minimizes () in which $\alpha_{k,j}$ is given by,

$$\alpha_{k,j}\left(P_{S_j}^t\right) = \Lambda \kappa_{k,j} P_{k,j}^R (P_{k,j}^S)\, T_{CP} \quad (13)$$

where, $\kappa_{k,j}$ is the pricing index decided by the relay node R_k for source node S_j and $P_{k,j}^R$ is the transmit power allocated by R_k to cooperate with source node S_j to reach the base station with data rate constraint Δ_{S_j} and BER constraint ξ_j. If the pricing index is 1, then the relay node just covers its cost that it incurs to cooperate with the source node. We explain the selection process of $\kappa_{k,j}$ in later sections. We can observe from equation (13) that $\alpha_{k,j}$ is a function of $P_{k,j}^S$ in the $S_j \rightarrow R_k$ link due to the BER constraint. Considering the BER expression given in equation (7), $P_{k,j}^R$ for a given $P_{k,j}^S$ can be expressed as,

$$P_{k,j}^R = \left(\frac{1}{2\left(\xi_j - \frac{0.5}{1+\Gamma_1}\right)} - 1\right)\frac{L(d_2)N_0\Delta_{S_j}}{\overline{h_2^2}} \quad (14)$$

where, $\overline{h_2^2}$ and d_2 are the channel power and T-R separation in meters respectively in the $R_k \rightarrow D$ link, and

$$\Gamma_1 = \frac{\overline{h_1^2} P_{k,j}^S}{L(d_2)N_0\Delta_{S_j}} \quad (15)$$

where, $\overline{h_1^2}$ and d_1 are the channel power and T-R separation in meters respectively in the $S_j \rightarrow R_k$ link.

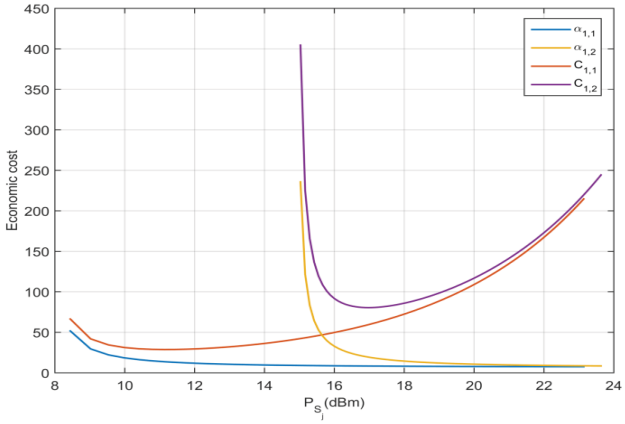

Fig. 2. The cost and bid function for relay number 1 and different source terminals in energy trading game.

Figure-2 shows the cost function given by equation (11) and $\alpha_{k,j}$ given by () for relay terminal 1 for two source terminals 1 and 2. There are only two source terminals shown in the graph for better comprehensibility, however it is noteworthy that each relay terminal computes these functions for all source terminals in the game. We can observe from the figure that $C_{k,j}$ is convex in $P_{k,j}^S$ and has a global minimum. Therefore, to minimize equation (11) and find the stationary point, we perform,

$$\frac{dC_{k,j}}{dP_{k,j}^S} = 0 \quad (16)$$

and isolating $P_{k,j}^S$, we get the closed form as,

$$\widehat{P_{k,j}^S} = \frac{L(d_2)N_0\Delta_{S_j}}{\overline{h_1^2}}\left[\left(\frac{1}{\xi_j}\right)\left(\sqrt{\frac{0.25\kappa_{k,j}L(d_2)\overline{h_1^2}}{L(d_1)\overline{h_2^2}}} + 0.5\right) - 1\right] \quad (17)$$

Therefore, the relay node calculates its $P_{k,j}^{R}$ from equation (14) and substitutes it in equation (13) to calculate the bid that needs to be sent to the source nodes $< \widehat{P_{k,j}^{S}}, \widehat{\alpha_{k,j}} >$. Now we explain how relay nodes select the source nodes that it responds to with a bid considering its transmit power constraint of $P_{k,max}^{R}$. For this, we start by defining the reward function of the relay nodes,

$$\Omega_{R_k} = \sum_{j} \Lambda(\kappa_{k,j} - 1)\, P_{k,j}^{R}\, T_{CP}\, x_{k,j} \qquad (18)$$

where, $x_{k,j}$ is the indicator function which takes the value one if the relay node R_k wins cooperation for source node S_j and takes the value zero otherwise. The strategy for the relay nodes would be to maximize Ω_{R_k} given it's transmit power constraint of $P_{k,max}^{R}$ Therefore, the relay nodes perform binary integer programming to maximize Ω_{R_k} given the constraint of $P_{k,max}^{R}$. The problem can be formulated as,

Maximize: Ω_{R_k}

Subject to:

$$(1) \sum_{j} P_{k,j}^{R} \leq P_{k,max}^{R} \qquad (19)$$

(2) $x_{k,j}$ is binary

The indicator $x_{k,j}$ selects the source nodes for each relay node. Now we explain how a relay node selects the value of $\kappa_{k,j}$ using reinforcement learning (RL). As mentioned before, we assume this game to be played every T_{CP} seconds. During the initial round, every relay terminal R_k choses a random number between 1 and 2 uniformly for $\kappa_{k,j}$. During the subsequent rounds, a relay node can revise its bids based on the information of whether it wins or loses its previous round with the source node. By means of RL, the relay nodes can use this learning to maximize their rewards by changing the value of $\kappa_{k,j}$. Therefore, if R_k wins cooperation with S_j in the present round, it can safely assume that its $C_{k,j}$ is lower than its competing relay nodes with respect to S_j. Hence, it can increase its $\kappa_{k,j}$ to increase its reward which is given by,

$$\kappa_{k,j}(t+1) = \kappa_{k,j}(t) + \omega_k^{+}; \quad \omega_k^{+} \in \mathbb{R}^{+} \qquad (201)$$

The value of $\kappa_{k,j}$ is increased in a greedy manner in the subsequent games until it loses a game at which time it reduces its $\kappa_{k,j}$, which is described below, and sets its $\kappa_{k,j}^{max}$ value above which the relay node does no increase $\kappa_{k,j}$. In the same way, if R_k loses cooperation with S_j in the present round, it knows that its $C_{k,j}$ is higher than its competing relay nodes and hence it decreases its $\kappa_{k,j}$ to try and win the game which is given by,

$$\kappa_{k,j}(t+1) = \kappa_{k,j}(t) - \omega_k^{-}; \quad \omega_k^{-} \in \mathbb{R}^{+} \qquad (212)$$

Note that no relay node reduces its value of $\kappa_{k,j}$ below one and $\kappa_{k,j}$ has a strict upper bound corresponding to the condition $C_{k,j} < \Lambda P_0^t$. Therefore, the energy trading game either converges towards the second price auction or towards the strict upper bound set by the condition $C_{k,j} < \Lambda P_0^t$.

Fig. 3 shows this convergence by means of the $\kappa_{k,j}$ values for different relay terminals with respect to source terminal 1 over the repeated game sequence. We can observe from the figure that relay terminal 2 has exploited its good channel conditions and increased its $\kappa_{k,j}$ value until game sequence number 19 at which relay terminal 4 wins one round. After that, relay terminal 2 sets it's $\kappa_{k,j}^{max}$ and does not increase its $\kappa_{k,j}$ value further. Thus the convergence is achieved with respect to source terminal 1.

B. Game Model 2 – Double Auction Game

In this section, we present the double auction game for multiple source terminals and multiple relay terminals for the objective to improve energy efficiency. We adopt the game theoretic model presented in [8]. In a double auction, the source terminals send their bids to the base station and the relay terminals send their-asks to the base stations. The auctioneer then decides which source and relay terminals are the winners of cooperation, the price that the source terminals need to pay and the payments relay terminals receive.

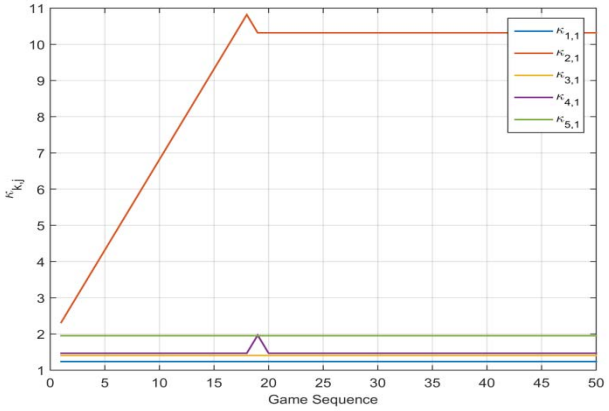

Fig. 3. $\boldsymbol{\kappa_{k,j}}$ values of the relay terminals for source terminal 1 over the game sequence.

We call the source terminals as buyers and the relay terminals as the seller. The buyers bid for the seller's services and the sellers ask for the cost of the resources they spend to cooperate. In this work, we consider all terminals to employ power control such as the overall bit error rate from the source terminal to the base station is maintained above ξ_j. The bids submitted by the buyers are calculated according to,

$$B_{S_j R_k} = \Lambda\left(P_{0,j}^{t} - P_{k,j}^{S}\right) T_{CP}\left(1 - \lambda_j\right) \qquad (22)$$

where, Λ is the base cost in Dollars/Joule known to every node in the network, $P_{0,j}^{t}$ is the power required to directly communicate with the base station, $P_{k,j}^{S}$ is the power required to communicate with the relay terminal R_k, T_{CP} is the cooperation period in seconds and λ_j is a uniform random number between 0 and 1 which is called as the "mark-up". The asks submitted by the relay terminals are calculated according to,

$$A_{S_j R_k} = \Lambda P_{k,j}^{R} T_{CP}(1 - \mathrm{H}_k) \qquad (233)$$

where, $P_{k,j}^{R}$ is the power transmitted by the relay terminal to communicate with the base station and H_k is a uniform random number between 0 and 1 called as "mark-up". After receiving all the bids and asks from the source and relay terminals respectively, the base station performs relay assignment algorithm which is described below. The problem of relay assignment in this case could be formulated as a linear programming problem given as,

$$\begin{aligned} &\text{Maximize:} && EE \\ &\text{Subject to:} && (1)\sum_{j} P_{k,j}^{R} \le P_{k,max}^{R} \\ & && (2)\ x_{k,j} \text{ is binary} \\ & && (3)\sum_{k} x_{k,j} \le 1 \\ & && (4) B_{S_j R_k} \ge A_{S_j R_k} \end{aligned} \tag{24}$$

where, we EE is the global energy efficiency given by,

$$EE = \sum_{j}\sum_{k} \frac{\Delta_{S_j}}{\left(P_{k,j}^{S} + P_{k,j}^{R}\right)T_{CP}} x_{k,j} \tag{25}$$

The unit of EE is bits/Joule. In the relay assignment, we allow a relay terminal to support multiple source terminals. However, we do not allow the source terminals to receive cooperation from multiple relay terminals. Also, a relay terminal is assigned to a source terminal only if the bid submitted by the source terminal is greater than or equal to the ask submitted by the relay terminal. After the relay assignment, the price to be traded is calculated using,

$$TP_{S_{j,}R_k} = \frac{B_{S_j R_k} + A_{S_j R_k}}{2} \tag{264}$$

In this case, we do not consider optimal power allocation with respect to the overall bit error rate probability between the source and the relay terminal. The bit error rate probability given by equation (8) is split equally between Π_1 and Π_2.

C. The Centralized Algorithm

In this section, we present the centralized algorithm in which the source terminals and relay terminals are assumed to send their true valuations and costs associated with cooperation to the base station. The base station then allocates the optimal relay assignment such that the energy efficiency is improved. The optimal relay assignment problem is formulated as a linear programming problem given by,

$$\begin{aligned} &\text{Maximize:} && EE \\ &\text{Subject to:} && (1)\sum_{j} P_{k,j}^{R} \le P_{k,max}^{R} \\ & && (2)\ x_{k,j} \text{ is binary} \\ & && (3)\sum_{k} x_{k,j} \le 1 \end{aligned} \tag{275}$$

We use the same definition for EE as described in equation (25). The linear programming problem is same as the one given in equation (24)(24) except in this case we do not have the bids and asks constraint. Moreover, in this centralized algorithm case, we consider optimal power allocation in addition to the optimal relay assignment.

IV. Simulation Results and Performance Analysis

In this section, we present the simulation results to compare the two game models described above with the centralized algorithm. For all the simulations conducted in this paper we use the parameters described below. The simulation plot size was chosen to be 600 x 250 meter's. We selected around 10 terminals, including relay and source terminals, in each simulation run. The base station was placed at (600,150). The source terminals were randomly placed between 0 and 200 in the x-axis and, 0 and 250 in the y-axis. The relay terminals were randomly placed between 100 and 300 in the x-axis and 0 and 250 in the y-axis. Fig. 4 shows one realization of the source and relay terminal locations in the simulation model. The source terminals were considered to be in NLoS conditions with the destination at all times and the relay terminals were considered to be in LoS conditions with the destination at all times.

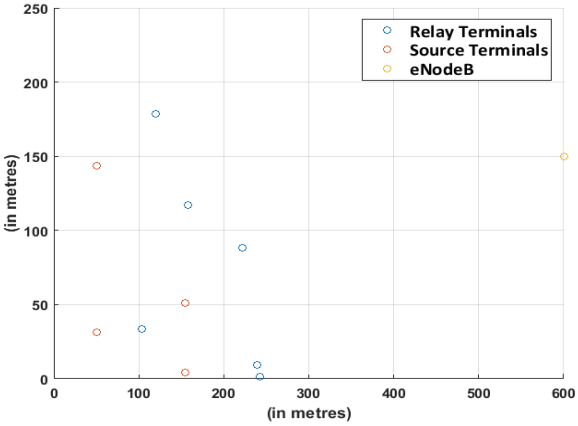

Fig. 4. An example of the realization of source and relay terminal locations in simulation model.

For the simulations, we use the same definition for global energy efficiency given by (25). Furthermore, to compare the two game models with the centralized algorithm we define θ as the normalized energy efficiency given by,

$$\Theta = 1 - \frac{\text{Energy spent with Relaying}}{\text{Energy spent without relaying}} \tag{28}$$

We performed Monte-Carlo simulations of 100 different scenarios with different terminal locations and different channel realizations. Table-2 lists all the parameters used in the simulations.

Fig. 5 shows the cumulative distribution function which compares the performance of the energy trading game, double auction and centralized algorithms for the improvement of energy efficiency. The CDF of the parameter Θ defined by

$$\textbf{CDF:}\ \ F_{\Theta}(\theta) = \Pr[\Theta \le \theta] \tag{29}$$

Provides the complete statistical information of the energy efficiency performance for the strategies considered here. From the figure, we can observe that centralized algorithm performs the best as expected.

TABLE II. SIMULATION PARAMETERS

Parameter	Value
BER	10^{-3}
$P_{k,max}^{R}$	23 dBm
Frequency	1.8 GHz
N_0	-163 dBm/Hz
h_{BS}	30 metres
h_{MS}	1.5 metres
Δ_{S_j}	400 kbps
ω_k^+	4
ω_k^-	4
Λ	1
T_{CP}	1 second
N	4 terminals
K	6 terminals

The energy trading game performs very close to the centralized algorithm. The double auction however does not perform as good as the energy trading game. This is due to the non-optimal power allocation between the source and the relay terminals with respect to the overall bit error rate probability which is due to the fact that the knowledge of the links between the source and the relay terminals is not present at the base station in a double auction game. Therefore, if this knowledge is assumed and if we assume truthfulness in the bids and asks in a double auction, the performance of the double auction game will approach the performance of the centralized mechanism.

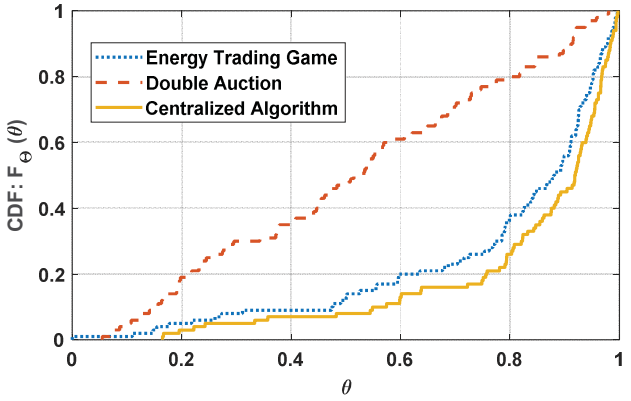

Fig. 5. Performance comparison between energy trading game, double auction and centralized algorithm for energy efficiency.

V. CONCLUSIONS

In this work we have studied the energy efficiency performance of radio access networks with terminal cooperation. We have considered two game theoretic approaches and have simulated the system to study the energy efficiency performance. The performance were also compared against the centralized approach when complete information is present at the decision making process. Our study shows that the game theoretic approaches can provide good energy efficiency in radio access systems when user terminals are helping each other. Our future work in this area includes the implementation of these techniques on hardware to provide proof of technology.

REFERENCES

[1] T. Tung et. Al Energy Efficiency Maximization for Downlink Cloud Radio Access Networks with Data Sharing and Data Compression, IEEE Transaction in Wireless Communication, Early Access, 2018

[2] P. Kyosti and e. al., "WINNER II Channel Models," 2008.

[3] S. Chandrasekharan, A. Al-Hourani, K. Magowe, L. Reynaud and S. Kandeepan, "Propagation Measurements for D2D in Rural Areas," in *IEEE 2015 ICC Workshops*, London, 2015.

[4] T. Rappaport, Wireless Communication: Principles and Practice, New Jersey: Prentice Hall, 1996.

[5] S. Kandeepan, S. Jayaweera and R. Fedrizzi, "Power Trading in Wireless Communications: A Cooperative Networking Business Model," IEEE Tran. on Wireless Communications, vol. 14, no. 3, pp. 1872-1880, May 2012.

[6] L. Xu and W. Zhuang, Energy-Efficient Cross-layer Resource Allocation for Heterogeneous Wireless Access, IEEE Trans. on Wreless Communications, Early Access , May 2018

[7] H. Zhang, et. al, Downlink Energy Efficiency of Power Allocation and Wireless Backhaul Bandwidth Allocation in Heterogeneous Small Cell Networks, IEEE Transaction on Communications, Vol 66, Iss 4, April 2018. pp 1705-1716

[8] D. Yang, X. Fand and G. Xue, "Truthful auction for cooperative communications," in Proceedings of the Twelfth ACM International Symposium on Mobile Ad Hoc Networking and Computing, 2011.

[9] N. Islam, S. Kandeepan and J. Scott, 'Optimal Rate Adaptation for Energy Efficiency with MQAM and MFSK', IEEE WPMC, Sydney 2014

[10] W. Zhang et. Al, Energy Efficiency Consideration for Indoor Femtocell Networks in TV White Spaces, IEEE Access, Vol. 6, pp 1565-1576, Dec 2017

[11] A. Hourani, E. Hossain and S. Kandeepan, 'Relay-Assisted Device-to-Device Communication: A Stochastic Analysis of Energy Saving', IEEE Transactions on Mobile Computing, Vol 15, Iss 12, Dec 2016

[12] A. Hourani, S. Chandrasekharan, A. Jamalipour, L. Reynaud, and S. Kandeepan 'Optimal Cluster Head Spacing for Energy-Efficient Communication in Aerial-Backhauled Networks', IEEE GLOBECOM, San Diego, Dec 2015

[13] S. Kandeepan et. al, "Energy Efficient Cooperative HAP-Terrestrial Communication Systems", Personal Satellite Service (PSATS) conference 2011, Malaga

[14] N. Islam, S. Kandeepan, and J. Scott, 'Energy Efficiency of Cellular Base Stations with Ternary-State Transceivers', IEEE ICSPCS, Gold Coast, Dec 2015